

AUTOMATIC IDENTIFICATION OF CRITICAL SCENARIOS IN A PUBLIC DATASET OF 6000 KM OF PUBLIC-ROAD DRIVING

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ABSTRACT

An increasing number of driving tasks in vehicles is being taken over by automation as automated driving technology is developed. An important aspect in this development is the safety assessment of new functions and systems. Scenario-based assessment is a promising tool, but it relies heavily on the availability of realistic scenarios for generating test cases.

Traditional methods take analyses from in-depth accident databases as a starting point to describe accident scenarios. In TNO's StreetWise methodology, the list of critical scenarios resulting from accidentology is expanded with scenarios that are identified from normal every day driving data. In this paper we describe a machine learning approach of automatic scenario identification in a dataset of public-road driving. The dataset together with the results will be made public to serve as a benchmark.

TNO will publish a dataset containing 6000 kilometers of driving on the public road, containing information on the ego vehicle CAN; the GPS position; information on the objects around the ego vehicle from radar and camera; and road lanes and lines. Furthermore, we propose a framework for automatic scenario extraction from real-world microscopic driving data, including measures of safety criticality.

Scenarios that are similar form a scenario class, currently we distinguish approximately 60 of such classes. Each instance of a scenario is described by a set of parameters that is specific for the scenario class. By analyzing large amounts of driving data, not only scenarios to fit in different classes are identified, but also the parameter values for each scenario instance are determined. This results in the frequency of occurrence of scenarios and the probability density function (PDF) for each of the scenario parameters. Metrics for safety criticality are defined based on time-to-collision, time-headway, post-encroachment time, etc. For each case, the safety criticality is evaluated based on the proposed metrics.

We have automatically identified two scenarios in the data: 1. Gap closing; 2. Cut-in of a vehicle in front of the ego vehicle. From the identified PDFs the nominal scenarios are identified as well as corner cases with parameter values

in the tail of the PDF. By changing parameter values within a realistic range around the corner cases, a check is made regarding their criticality.

The two scenarios that are identified describe only a small part of the total number of kilometers driven. However, the bottom up approach to scenario mining described here can be extended to more scenarios in a relatively straightforward way, with the goal of describing the entire dataset with scenarios.

Automatic scenario mining from driving data is an essential step towards safety validation of AD functionalities. TNO publishes a dataset with 6000 kilometers of public-road driving, for which we show that it is possible to identify critical scenarios, in addition to nominal scenarios, even if in these kind of studies critical situations are rare.

INTRODUCTION

Automated driving (AD) functions are considered an important tool for increasing road safety and comfort, reducing emissions and improving traffic flow. The increase in automation requires a different protocol for quality and performance assessment of vehicles than traditionally done [1][2][3]. For this, a scenario-based approach has been proposed [4][5]. The collection of scenarios used for defining test cases should represent and cover the entire range of real-world traffic situations that might be encountered by the AD system under test. In the TNO StreetWise methodology, scenarios are extracted from real-world microscopic traffic data, and are used to build a database suitable for testing and validation of automated driving functions [6]. The use of real-world scenarios for testing purposes requires accurate scenario extraction methods from driving data, to ensure representativeness of the scenario database. In order to facilitate a comparison between different scenario-mining methods, a public benchmark dataset would be a valuable tool.

Several public public-road driving datasets already exist. The Oxford robotcar dataset contains data of 100 repetitions of the same route in Oxford, UK [7]. The sensors that were used on the recording vehicle include multiple cameras, LIDAR and GPS, but no sensor fusion has been performed on the raw data. Hence, no object level data is available from this dataset. For the Next Generation Simulation (NGSIM) program¹, data was collected at several US highways with a network of synchronized digital video cameras, from which vehicle trajectory data was extracted. This provides a bird's eye view of specific portions of road. The Apollo obstacle trajectory prediction dataset² contains data collected with LIDAR, cameras and GPS. The data has been turned into features that can be used to train a Machine Learning algorithm on the provided labels on the intention of the other road users.

In this work we present a dataset of public-road driving for benchmarking scenario-mining algorithms. This dataset is available at www.tno.nl/streetwise. Unlike the previously mentioned public datasets, this dataset contains object-level data from an in-car perspective that can be directly used to identify scenarios in the data. As a first benchmark, we present the results of a scalable approach to scenario mining, based on fundamental building blocks describing the trajectories of all road users. Two scenarios are shown as example, 'gap closing' and 'cut in'. As scenario-mining algorithms are continuously improved, progress can be measured on this public dataset. Finally, we show how a scenario database of driving data can be used to assess the safety criticality of the scenarios found in the data.

METHOD

Real-world data logging

TNO recorded data from 20 different drivers between 25-60 years old, all of whom had their driving license for more than 5 years and are driving more than 5000 km per year. They drove together about 6000 km in mixed traffic, of which approximately half in manual mode and half in ACC mode. All driving was performed during the day time (from 8:30 to 17:00) under dry weather conditions.

A dedicated specially prepared vehicle (Toyota Prius) was used for the tests. The vehicle records information from the following sensors:

¹ <https://data.transportation.gov/>

² <http://data.apollo.auto/>

- Vehicle CAN (velocity / accelerations / yaw rate / steering wheel angle / wheel speeds)
- Mobileye camera (object / lane information)
- Continental-30x radar front centre, rear left, rear right
- U-blox GPS
- Ibeo LIDAR

The position and viewing angle of the sensors is depicted in Figure 1. Besides these sensors also an additional forward-facing camera was used to record reference footage. The LIDAR has not been used in the analysis of the data.

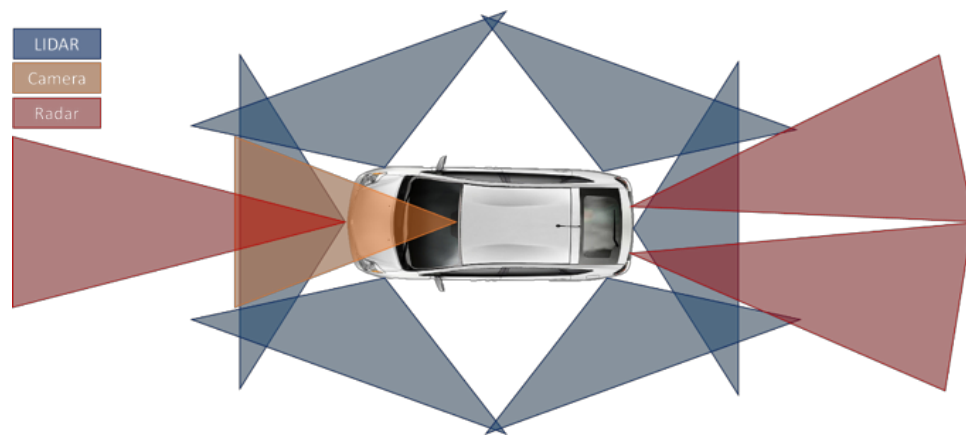


Figure 1: Field of view of the external sensors of the recording vehicle. Orange: front-looking Mobileye camera. Red: Continental-30x radar, front centre, rear left, rear right. Blue: Ibeo LIDAR.

Data pre-processing

The recorded data is converted to a uniform representation (the so-called world model) of the static and dynamic environment around the ego vehicle. In this dataset the static environment is only represented by the road markings of the ego lane. The lateral position of all road users is considered relative to these lanes. The output of the Mobileye camera is used for the road markings. This contains the type of lane marking and predicted position of the marking with certain confidence level.

The dynamic traffic is modelled with a multi-target tracker that has been developed by TNO [8]. The multi-target tracker uses the sensor output of the Mobileye camera and the 3 Continental radars (front center, rear left and rear right radar). The test vehicles were also equipped with Ibeo LIDARs, but those were not used. The multi-target tracker fuses the sensor data and provides the position and motion of detected objects. The targets are represented as points. The distance between the ego vehicle and a target in front of ego vehicle is the distance between target vehicle rear bumper center and ego vehicle front bumper center. For the distance between the ego vehicle and a target behind the ego vehicle the distance between target vehicle front bumper center and ego vehicle rear bumper center is used. For lateral position the center of the vehicle (both ego and target) is used as reference point.

The test drivers drove a fixed route in the region of Amersfoort in the Netherlands. The route has a length of approx. 46 km and takes about 50 minutes driving without delays. About 55% of the distance is highway, 40% is rural and the remaining 5% is urban area. About 55% of the route are multi-lane uni-directional roads. The route and driving direction are shown in Figure 2. Every test person drove the route 6 times, 3 times with ACC and 3 times without.

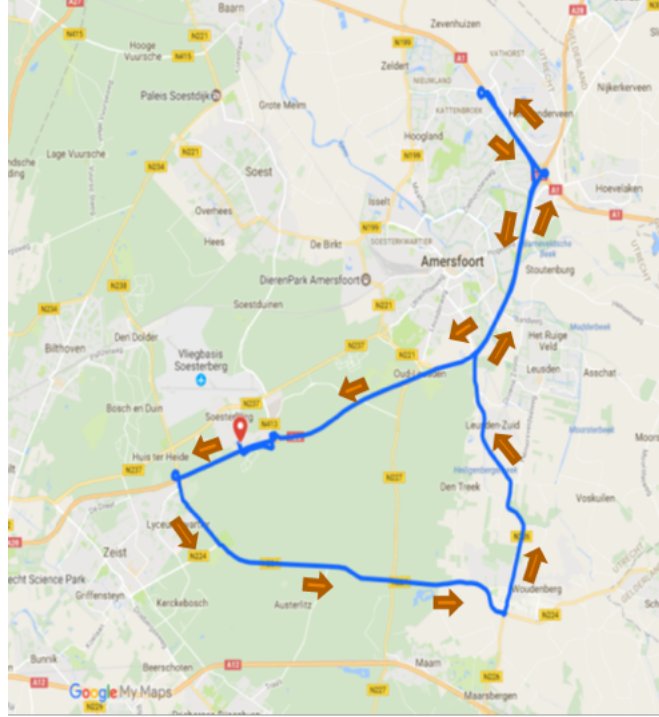


Figure 2: The route, including driving direction, that was driven by the test drivers.

Identification of scenarios

In the StreetWise methodology traffic is interpreted as a sequence of scenarios, meaning that every instance of the data is assigned to a scenario [6]. These scenarios need to be defined by a consensus among experts in order to make them as useful as possible for testing. In this work we focus on two relatively straightforward scenarios: one scenario that is centered on longitudinal interaction between two vehicles, and one centered on lateral interaction. The first scenario is the ‘gap-closing’ scenario. It consists of a target vehicle in front of the ego vehicle that is in the same lane as the ego and decelerates. This scenario ends when the distance between the two vehicles no longer decreases. The second scenario is the ‘cut-in’ scenario. In this scenario a target vehicle moves from an adjacent lane to the ego lane in front of the ego vehicle, such that the target becomes the lead vehicle of the ego vehicle. Figure 3 shows a graphical representation of the two scenarios.

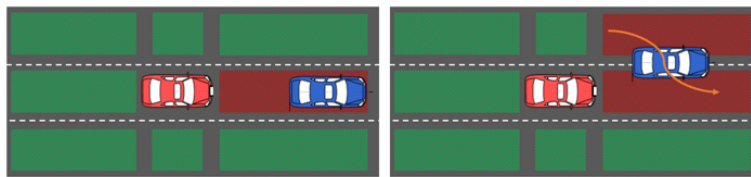


Figure 3: *Left:* Gap-closing scenario. *Right:* Cut-in scenario.

As described in [6], we define activities as building blocks and construct scenarios by combining activities of different road users. Activities can fall into two categories: longitudinal and lateral. Longitudinal activities can be either acceleration, cruising or deceleration. Lateral activities are defined with respect to the lane and can be either lane following, turn (or lane change) left or turn (or lane change) right. These 6 activities cover all the allowed movement of a vehicle on the road and are sufficient to describe any possible trajectory. The activities are identified in the data for the ego and all the targets that are detected around the ego. The trajectory of a road user is described by at least two (i.e. longitudinal and lateral) activities at all times.

Scenarios are found by combining activities with the relative position and speed of every target. We use template matching on a graphical network to efficiently find the scenarios in the dataset. In this bottom-up approach, given

the right template to search for, any scenario can be detected straightforwardly without the need to write a separate algorithm for every scenario. The activity detection and scenario mining algorithms will be detailed in a forthcoming publication.

Identification of critical scenarios

For all scenarios the minimal set of parameters needed to describe the activities and the scenarios is stored. This includes a full description of the time evolution of every activity of the ego and every target, the relative positions of the targets with respect to the ego, the relative speeds of the targets with respect to the ego, and the absolute position of the ego. This set of parameters can be used to determine the safety criticality of the scenarios found in the data. Many possible safety indicators have been proposed [9][10]. As an example, we consider in this work the following safety criticality indicators:

- Start longitudinal distance [m]: the longitudinal distance between the ego and the target at the start of the scenario.
- Maximal deceleration during the scenario [m/s^2].
- Minimal Time-To-Collision (TTC) [s]: the time to collision is the time it takes for the rear vehicle to cover current longitudinal distance between rear and front vehicle, also taking into account the possible distance covered by front vehicle. The TTC is computed in the following way:

$$\text{TTC [s]} = \text{inter-vehicle-distance [m]} / (\text{rear vehicle velocity} - \text{front vehicle velocity}) [\text{m/s}].$$
- Maximal lateral speed during the scenario [m/s].

RESULTS

We have applied the scenario identification algorithms to the 6000 km of public-road driving. In this section we describe the results and give an example of the analysis of criticality of a scenario based on the safety criticality indicators described in the previous section.

Braking in front

We have identified 1460 braking in front scenarios in the data. An example of the relevant signals for this scenario is shown in Figure 4. The target vehicle has initially a higher speed than the ego, before it starts decelerating. About 1 second after the longitudinal distance starts the decrease, the ego vehicle decelerates until the distance between the vehicles is 8 meters, at which point the target accelerates again.

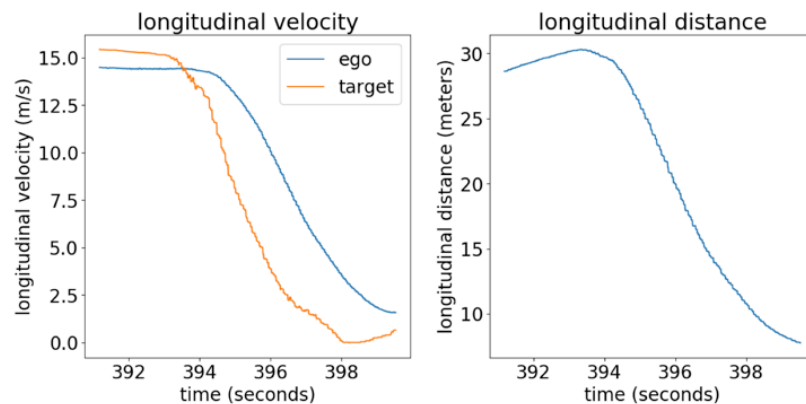


Figure 4: *Left:* Longitudinal speed as function of time for the ego and the target. *Right:* Inter-vehicle distance as function of time.

By comparing the safety criticality parameters of this scenario with the probability density functions (PDF) of these parameters constructed from all scenarios in the data, the relative safety criticality of this scenario can be assessed.

In Figure 5 the longitudinal distance at the start of the scenario, the maximal deceleration of the target and the minimal TTC are shown.

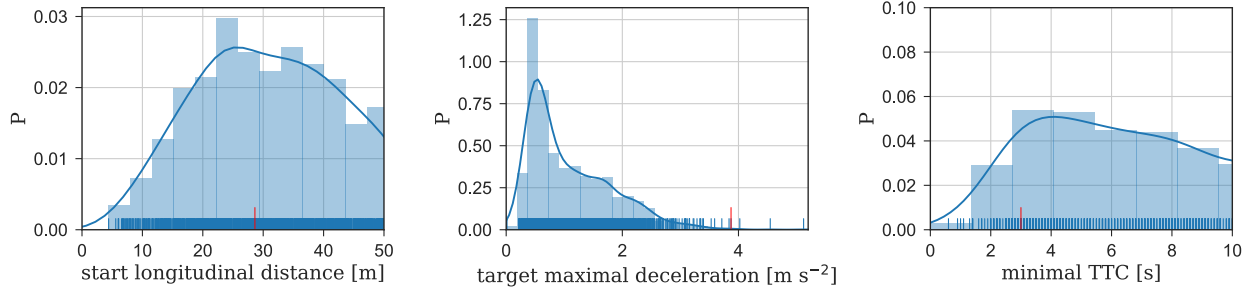


Figure 5: Probability densities of safety indicators for the braking-in-front scenario. Solid line is a univariate non-parametric fit of the histogram with Kernel Density Estimation using a Gaussian kernel. Vertical lines on the x-axis denote the data points. The red vertical line indicates the example shown in Figure 4. *Left:* Longitudinal distance at the start of the scenario. *Centre:* Maximal deceleration of the target during the scenario. *Right:* Minimal time to collision during the scenario.

The maximal deceleration of the target is among the highest found in the dataset. However, due to the relatively high inter-vehicle distance at the start of the scenario, this does not result in a safety critical scenario. This is reflected in the minimal TTC that is above 2 seconds. The drawback of only using the TTC for safety analysis is that it is not always defined, even in cases where the target might still be dangerously close to the ego [9]. This analysis shows that it is not sufficient to rely on a single parameter to judge the safety criticality of a scenario.

Cut in

We have identified 403 cut-ins in the dataset. An example of a cut-in scenario with the relevant signals is shown in Figure 6. The lateral speed of the target increases at the start of the scenario indicating the lane change. Although the longitudinal speed of the target is initially much lower than that of the ego, the target quickly accelerates and as a result the longitudinal distance is never less than 17 meters during the scenario.

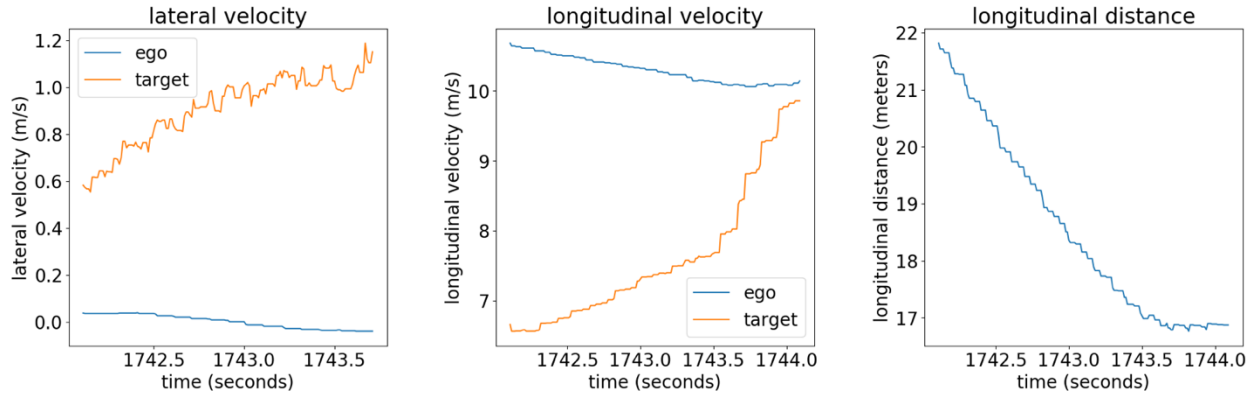


Figure 6: *Left:* Lateral speed as function of time for the ego and the target. *Centre:* Longitudinal speed for the ego and the target. *Right:* Inter-vehicle distance as function of time.

To determine the safety criticality of this example, in Figure 7 we show the PDFs of 3 safety indicators. These indicators show that even though the lateral speed of the target was relatively high and the longitudinal distance at the start of the scenario was below average, this example is not safety critical, as the minimal TTC of more than 5 seconds shows. However, as noted earlier, relying only on TTC for defining safety criticality has severe drawbacks.

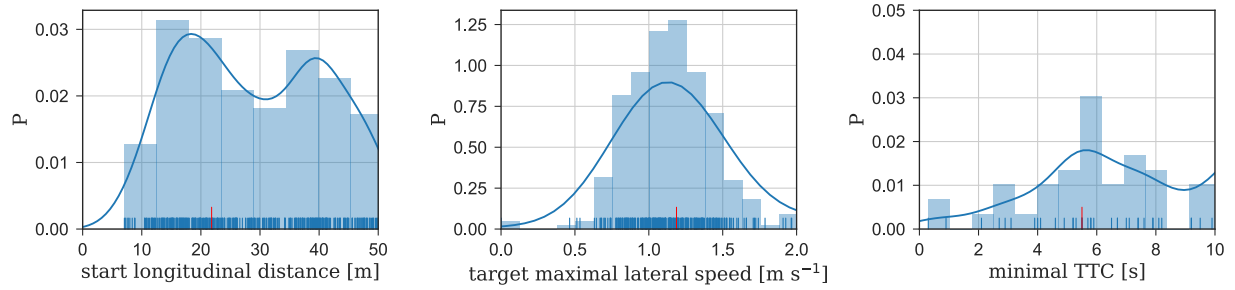


Figure 7: Probability densities of safety indicators for the cut-in scenario. Solid line is a univariate non-parametric fit of the histogram with Kernel Density Estimation using a Gaussian kernel. Vertical lines on the x-axis denote the data points. The red line indicates the example shown in Figure 6. *Left*: longitudinal distance at the start of the scenario. *Centre*: Maximal lateral speed of the target during the scenario. *Right*: Minimal TTC during the scenario.

CONCLUSIONS AND DISCUSSION

We have presented a dataset of driving on the public road that consists of 6000 kilometers of a mix of highway (55%), rural (50%) and urban (5%) driving and contains information on the ego vehicle CAN; the GPS position; information on the objects around the ego vehicle from radar and camera; and road lanes and lines. The dataset will be made publicly available at www.tno.nl/streetwise.

In addition, we have presented the results of a bottom-up approach to scenario mining in this dataset. By first detecting activities in the data that serve as building blocks, scenarios can be identified in the data in a scalable manner. With the input of experts about what a certain scenario entails, a template of the scenario can be defined that can immediately be used in the scenario mining algorithm to extend the scenario catalogue. The two scenarios described in this work only describe a very small portion of the data, but we expect to add more scenarios in the near future, working towards the goal of assigning every instance of data to at least one scenario.

Finally, we have presented a method for determining the safety criticality of scenarios based on the probability density functions of a set of safety indicators. By comparing where different safety indicators are in the distributions of all scenarios, the safety criticality of the scenario can be quantified. The dataset presented in this paper is too small for a thorough statistical analysis and does not contain any critical scenarios, we plan to extend the analysis with more data in the future.

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